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The effect of mixed orientation on the accuracy of a forecast model for building integrated photovoltaic systems

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Abstract

BIPVs (Building Integrated Photovoltaics) are expected to dominate the solar industry in urban areas, especially in connection with zero-emission buildings. They allow the use of mixed orientations which result in multiple generation peaks throughout the day that can precisely match the consumption profile of the building. Multiple generation peaks however make the design of an accurate PV (Photovoltaic) output power forecasting tool a complex task. This paper, therefore, aims to quantify the effect of these mixed orientations on the accuracy of such prediction models for a 181.15 kWp BIPV located in Trondheim, Norway. The results show that a forecast model that has a complete perception of all the mixed orientations reduced the RMSE (Root Mean Squared Error) forecast error by 34%. The findings in this work have important implications for developing a practical energy management system that is common in the operation of BIPVs.

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Keywords: Photovoltaic power forecasting; Building integrated photovoltaics; Zero emission building; Mixed orientations; Deep learning

1. Introduction

Electricity generation from wind and water dominates the Norwegian power system. According to the data from the Statistics of Norway, the above two sources accounted for approximately 99% (i.e., 155.467 TWh) of total generated electricity in 2021. The remaining 1% is mostly a contribution from thermal power plants. As of 2021, the contribution of solar electricity is almost insignificant (0.14 TWh). However, as it can be seen from Fig. 1(a), which shows the yearly installed capacity growth of PV (Photovoltaics) in Norway for the past 5 years, and Fig. 1(b), which shows the expected electricity generation from various sources in 2040 [1], the contribution from solar will be meaningful in the coming few years. According to this projection, solar power will contribute as much as 6 TWh of electric energy by the year 2040.

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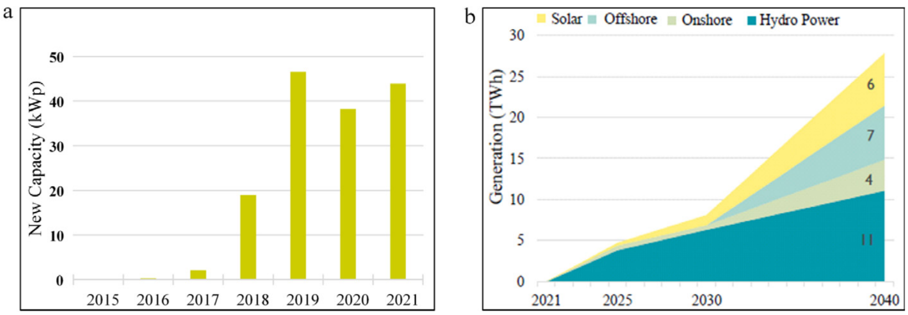

Fig. 1. (a) PV capacity growth in Norway; (b) The expected electricity generation in Norway 2021–2040.

So far, the largest contributors to the solar power capacity in Norway are large (>15 kWp) PV plants on rooftops. Future growth is expected to be seen in relation to the use of PV systems in industries, in large office and commercial buildings, zero emission buildings, floating PV (in hydropower reservoirs), and agro PVs. The use of PV systems in connection with large buildings in urban areas is quite interesting in terms of the economic, aesthetic, and technical advantages it offers. This can be done in two ways: BIPV (Building Integrated PV) and BAPV (Building Applied PV).

BAPV involves fitting PV modules to existing surfaces via superimposition after the construction is completed. On the other hand, BIPV is the replacement of conventional building materials with materials incorporating PV modules in parts of the building such as the roof and facade. These kinds of architectures allow the use of mixed orientations (different tilt and azimuth angle) which result in multiple generation peaks throughout the day that can precisely match the consumption profile of the building. This work focuses on a BIPV system located in Trondheim, Norway.

In the same way as most other PV systems, BIPVs are integrated with the power grid. They must satisfy both the technical and economical requirements of the grid. However, due to the irregular nature and the high sensitivity of the PV power to meteorological conditions, the high penetration of these systems brings challenges to the operation of the existing grid [2]. The current grid was not designed to accommodate these renewable energy sources and the inherent variability of solar power creates a constant challenge in meeting variable load with variable supply.

The use of an ESS (Energy Storage System) together with an AI (Artificial Intelligence) -based PV output power forecasting model is seen by many as a cost-effective means to overcome the limitations of BIPVs [3,4]. Accurate PV output power forecasting enables proper scheduling and operation planning, allows precise energy trading decisions in power markets, and significantly reduce the cost and size of the required balancing reserves. In addition, accurate prediction of the PV output power is an important element in the design of an optimal energy management framework that can ensure maximum benefits from ESS while satisfying the grid requirements [5].

The design of PV output power forecasting models based on AI algorithms has been the focus of various studies in the last two decades. AI algorithms such as random forest [6], gradient boost [7], support vector machines [8], artificial neural networks [9], convolutional neural networks [10], and LSTM (Long Short-term Memory) [11] have been used successfully to design a precisely accurate prediction model. All the above approaches are data-driven techniques that solely depend on the measurement of output power and the availability of weather parameters without considering the physical orientation of the PV modules.

In BIPV the various PV modules are oriented with different tilt and azimuth angles. This result in multiple generation peaks and falls which is suitable for matching the consumption profile of the building but this also makes the design of a forecasting tool that can track all these peaks and falls a challenging task. In general, prior works are focused on the design of a better forecasting model based on AI algorithms and the study of the impact of tilt and azimuth angle variations on the annual yield of a photovoltaic system [12–14] independently. The interaction between the two problems has received little or no attention in the literature.

To address this previously unaccounted issue, this work, therefore, aims to quantify the effect of these mixed orientations on the accuracy of a PV output power prediction model for a 181.15 kWp BIPV located in Trondheim, Norway. This work is part of a PRESAV (Predictive Control for Active Heat Storage in Building) financed by FME ZEN (https://fmezen.no/), which develops various predictive control strategies for active heat storage accounting for electricity price, district heating price, weather forecast, and local heat demand in buildings with installed BIPVs and active heat storage. The result from this work will serve as a significant input for the design of various control strategies based on model predictive control.

The rest of this paper is organized as follows. Section 2 presents the description of the system considered in this work, the impact of the orientation of the PV modules on the output power profile, and the different approaches that are used to quantify the impact of mixed orientation on the performance of a prediction model. A brief description of the algorithm used to design the prediction model is also included in this section. The results from this work are presented and discussed in Section 3 and important conclusions are made in Section 4.

2. Methodology

2.1. System description

The logical layout of the BIPV system considered in this work is shown in Fig. 2. It is located at ZEB (Zero Emission Building) lab, which is a laboratory for zero-emission buildings in Trondheim, Norway. It consists of PV modules arranged in six different orientations (Table 1). They are connected to three DC/AC inverters and the grid through three control units. The orientation and detailed capacity of these PV modules are shown in Table 1. PV output power data from each orientation is collected from the plant with a granularity of 15 min. Meteorological data including solar radiation and temperature is also obtained for the same period from a weather station on the site.

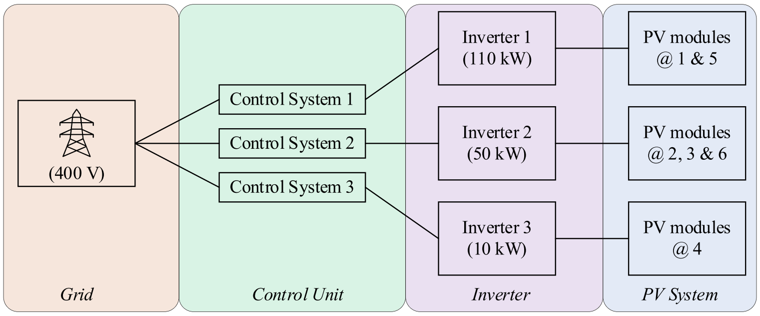

Fig. 2. Logical topology of ZEB lab PV system.

Table 1. Description of the PV system at the ZEB lab.

Orientation	Location	Capacity (kWp)	Area (m^2)
1	Roof	98	456.3
2	North Façade	11.25	53
3	South Façade	22.36	144.2
4	West Façade	12.365	79.6
5	East Façade	24.47	156.2
6	Pergola	12.705	74.1

2.2. The effect of mixed orientation

The two most important physical parameters that significantly affect the energy yield from photovoltaic systems are tilt angle (β) and azimuth angle (γ). These parameters have a considerable impact on the amount of solar radiation that reaches the photovoltaic modules and thus affecting the generated energy. For fixed-mounted PV modules, the tilt angle is the angle between the horizontal plane and the PV module. The azimuth angle indicates the compass direction from which the sun's radiation is reaching the PV module. For a module facing south, the sun is located directly above the module at solar noon ($\gamma = 0$). The tilt angle affects the period/season where the energy yield is optimal whereas the azimuth angle impacts the daily generation profile of the PV system.

The effect of these two parameters on the output power of a BIPV can be seen in Fig. 3. This figure shows how multiple generation peaks are occurring because the PV modules are oriented differently, facing east, west, south, and north in this case. This observation suggests that these multiple generation peaks could significantly impact the performance of a PV output power forecast model. To study this, three forecast models at three different system levels are analyzed in this work.

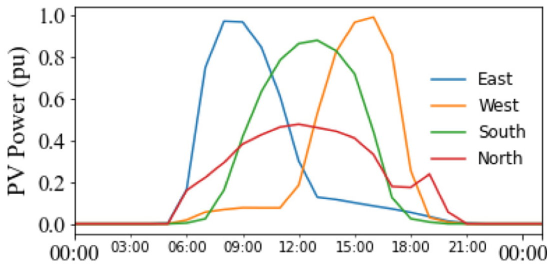

Fig. 3. The effect of mixed orientation in PV output power (14/04/22).

2.3. Forecast model based on LSTM

To quantify the impact of the mixed orientation of PV modules on the accuracy of a PV output power forecast model in BIPVs, three different set-up configurations were used. In the first case, a forecast model is designed on the system level where the total PV output power from the building is used to train a single forecast algorithm. In this way, the algorithm is unaware of the mixed orientations. In the second case, three forecast algorithms are trained based on the data from the three inverters. The PV modules in different areas of the building are aggregated according to the layout in Fig. 2. The third case trains six different forecast algorithms for each orientation in the system. The main advantage of this approach compared to the previous two is that the model has a complete perception of all the mixed orientations. All three cases are shown in Fig. 4.

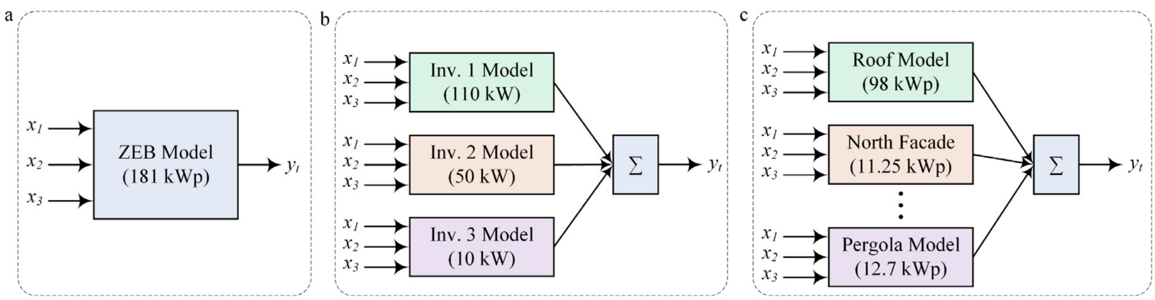

Fig. 4. (a) System level model (Case 1); (b) Inverter level model (Case 2); (c) Orientation level model (Case 3).

It is important to note that developing a highly accurate forecast model is not the main purpose of this work, it is only included here for completeness. A deep learning model based on the LSTM network was used in all three cases. LSTM is a popular family of recurrent neural networks and is an ideal candidate for modeling time-dependent and sequential data problems, such as PV output power prediction. It solves the problem of vanishing gradient that enables the learning of long-term dependencies possible. LSTM was selected for its performance in terms of statistical metrics as reported in [11,15].

3. Result and discussion

In this work, the impact of mixed orientations on the performance of a 15 min ahead PV output power forecast model based on the LSTM network is analyzed for a BIPV plant located at the ZEB living lab, Trondheim, Norway. Of the total 11,616 samples of data, 90% was used for training and the remaining 10% was used as a test dataset.

The performance of each model was evaluated using the *RMSE* (Root Mean Squared Error) and *WAPE* (Weighted Absolute Percentage Error). These metrics are defined as shown in Eqs. (1) and (2) respectively.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(P_a - P_f)^2} \tag{1}$$

$$WAPE = \frac{1}{N}\sum_{i=1}^{N}\frac{|P_a - P_f|}{\sum_{i=1}^{N} P_a} \tag{2}$$

where P_a and P_f are the actual and forecasted PV power and N is the number of samples in the test data set.

Table 2. Performance of various modeling approaches.

Case	RMSE (kW)	WAPE (%)
1	3.392	7.466
2	2.333	4.998
3	2.242	4.664

The results obtained from this study are shown in Table 2. This table summarizes the impact of mixed orientation on the performance of a forecast model in terms of RMSE and WAPE. The results demonstrate that the PV output forecast model which has prior knowledge of all the mixed orientations in the BIPVs (Case 3) has the smallest RMSE and WAPE errors. 2.242 kW and 4.664% respectively. This result is an important finding of this study, and it appears to tally with the hypothesis in Section 2.2. Multiple generation peaks that occur as a result of mixed orientations can significantly affect the performance of a prediction model if not taken into consideration.

Considering Case 1 as a base model, the improvement in the performance of a forecast model can be quantified using Table 2. As it is apparent from the table, the performance improvements achieved by using a forecast model on an inverter level (Case 2) and orientation level (Case 3) are significant. Reduction of RMSE error by 31% and 34% was achieved for Case 2 and Case 3 respectively. Similarly, a reduction of WAPE by 33% and 37% were also obtained. This again strongly agrees with the hypothesis in Section 2.2.

Fig. 5 shows the plot of the actual and predicted PV output power for two consecutive days in the test dataset. A closer examination of this figure reveals that in contrast to Case 1 and Case 2, the forecast model in Case 3 is able to capture the fast and abrupt changes in the PV output power. A possible explanation for this result could be that the forecast model is aware of all the orientations and can predict their peak generations precisely.

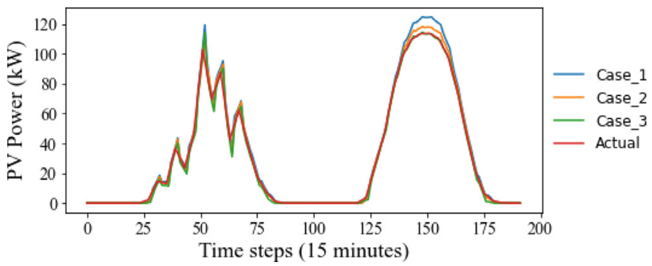

Fig. 5. Actual vs. forecasted PV output power for two consecutive days in the test dataset.

4. Conclusion

This work aimed at analyzing the effect of mixed orientations on the accuracy of a PV output power prediction model for a 181.15 kWp BIPV located in Trondheim, Norway. The results from this study indicate that a forecast model that takes into account all the various orientations (Case 3) in BIPVs has a better performance than a forecast model on a system and inverter level. BIPVs have huge potential in generating electricity that matches the consumption profile of a building. Their full potential can be realized, and their adoption can be facilitated by using accurate PV output power forecasting models. This work therefore can serve as the groundwork for future research into techniques and approaches that can result in a high-performing forecast model for BIPVs.

Declaration of competing interest

We, the authors of the paper hereby declare that we have no conflicts of interest to disclose that are directly or indirectly related to the research presented in this manuscript.

Data availability

The authors do not have permission to share data.

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